DOI: 10.61782/fa.2025.0714

FORUM ACUSTICUM EURONOISE 2025

PSYCHOACOUSTIC MODELLING OF AVAS SOUNDS: CONSUMER-CENTRIC SEMANTIC ATTRIBUTE DEVELOPMENT FOR ELECTRIC VEHICLES

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ABSTRACT

This work presents the development of semantic attributes for Acoustic Vehicle Alerting Systems (AVAS) in electric vehicles, using psychoacoustic modeling and consumer preference analysis. Participants from different consumer groups were exposed to a series of AVAS sound samples and assessed them by means of semantic differentials. Preference classification across groups of consumers, together with correlation of the insights obtained with psychoacoustic parameters, is proposed in this paper to provide actionable guidelines for the optimal design of AVAS. The findings contribute to enhancing pedestrian safety and user experience while aligning with regulatory standards.

Keywords: *electric vehicles, semantic attributes, psychoacoustics*

1. INTRODUCTION

The rise of electric vehicles (EVs) has introduced challenges to the vehicle sound design. Unlike traditional internal combustion engine (ICE) vehicles, EVs operate silently, especially at low speeds, creating safety risks for pedestrians and other road users. To solve these problems, regulatory authorities worldwide have mandated the integration of Acoustic Vehicle Alerting Systems (AVAS) in EVs to ensure audibility at low speeds. However, the design of these artificial soundscapes is a challenge, requiring the balance of safety, consumer preferences, regulatory compliance, and low annoyance levels.

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Figure 1: AVAS recordings were taken in a low traffic/ noise area in Radeberg, Germany (population < 20,000).

This research uses the foundational work of Altinsoy and Jekosch [1], which introduced "semantic space" for vehicle sounds. Their framework for developing semantic differentials describes vehicle sounds in terms of customer perceptions, showing that technical sound metrics alone cannot convey user experience. The study's methodology for validating semantic descriptors has become the status quo in the field of vehicle sound design. However, their research focused on ICE vehicles and did not fully solves the challenges created by EVs and their AVAS systems.

Furthermore, previous research didn't address cross-user group preferences and cultural variability in sound perception. While [2] explored the role of emotional and multimodal associations in sound design, demographic and psychographic factors such as age, driving habits, and cultural differences remain underexplored. Additionally, the work conducted in [3] pointed out the limitations of using expert listeners, showing the need for consumer-driven approaches that reflect the population's preferences.

To address these gaps, this paper proposes an approach that integrates psychoacoustic modeling with semantic differential analysis to capture consumer perceptions of AVAS sounds. By exposing participants from diverse consumer groups to AVAS sound samples and collecting data on their preferences through semantic scales, this study links psychoacoustic parameters to relevant consumer descriptors. The findings extend the framework of [1] to the domain of EVs and provide guidelines for designing AVAS sounds. The goal is to enhance pedestrian safety and apply user preferences together with regulatory requirements.

Moreover, the inclusion of diverse participant groups addresses the cultural and demographic variability noted by [2], ensuring that the resulting AVAS soundscapes are globally acceptable. The focus on emotional and functional attributes, such as "calm," "futuristic," and "powerful," as published in prior works, bridges the gap between technical sound metrics and consumer-driven data. By building upon the status quo established by [1], this research builds on the state of the art in AVAS sound design, contributing to more harmonious urban soundscapes.

2. METHOD

2.1 AVAS Sound Recordings

A dummy head (Head HSU III.3) was placed 2 m from the center of the vehicle at a height of 1.2 m to record the driving-by sounds in the test-track environment complying with the UNECE R138 requirements for AVAS sound measurements. Fig. 1 gives a representation of the test track. Tab. 1 shows the vehicle models which the sounds were recorded and the corresponding FFT vs. time spectrograms are given in Fig. 2. Spectrograms of the vehicles were calculated using Artemis Suite 13.6.

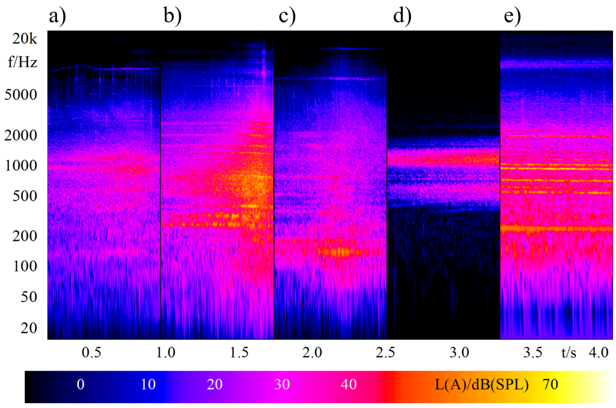

Figure 2: FFT vs. time spectrograms generated from the EV AVAS sounds used in the listening tests: a) BYD Atto 3 b) Scania 25P c) Cupra Born d) Polestar 2 e) KIA EV.

Table 1: Vehicle information for the sounds played to the participants

Nr.	Vehicle Model	Vehicle Type	Vehicle Speed
1	Cupra Born	E-Car	10 km/h
2	BYD Atto 3	E-Car	10 km/h
3	KIA EV	E-Car	20 km/h
4	Polestar 2	E-Car	20 km/h
5	Scania 25P	E-Truck	20 km/h

2.2 Participants and the Online Surveys

To investigate consumer perceptions of AVAS sounds in EVs, an online survey was conducted with individuals having prior exposure to EVs, either by seeing or hearing them. Online survey's are proven to be reliable when sound quality related studies are executed [4]. The study works on how different demographic and psychologi-

Table 2: Factor loadings of descriptors on components based on PCA. The adjectives are shown in the table in the same order as they were presented to the participants in the survey.

Descriptor	Component 1	Component 2	Component 3
Soft - Hard	**0.901**	-0.143	-0.076
Booming	**0.784**	-0.275	0.019
Weak - Powerful	**0.796**	-0.176	0.261
Humming	**0.716**	0.241	0.199
Roaring	**0.868**	-0.265	0.184
Calm - Aggressive	**0.854**	-0.124	-0.242
Thin - Thick	**0.751**	-0.300	0.212
Fine - Harsh	**0.806**	-0.186	-0.066
Quiet - Loud	**0.877**	-0.045	-0.154
Rattling	**0.827**	-0.086	0.195
Buzzing	**0.778**	0.241	0.141
Purring	**0.742**	0.098	0.393
Slow - Fast	**0.533**	0.284	0.346
Clattering	**0.832**	0.020	0.001
Truck-like - Car-like	-0.301	0.399	0.077
Annoying	**0.582**	0.130	**-0.571**
Howling	**0.775**	0.130	0.095
Turbine-Like	**0.579**	-0.041	-0.235
Hissing	0.462	**0.542**	-0.391
Whistling	0.479	**0.599**	-0.282
Low - High	**0.605**	0.366	-0.322
Strained - Effortless	0.232	-0.091	**0.511**
Robust - Rickety	**0.558**	0.123	-0.174
Electric-like	-0.116	**0.686**	0.318
Futuristic	-0.072	**0.751**	0.362

cal factors influence the subjective evaluation of AVAS sounds, connecting psychoacoustic parameters and user-driven preferences. Participants also provided information about problems such as EV range and availability of charging stations. A total of 29 participants (22 males, 7 females / ages between 18 to 65) joined to the online survey.

The survey was divided into two sections. First, participants entered their demographic and background information, including their age, gender, education level, income, and country of residence. They also answered questions about their experience with EVs, driving habits, and whether they currently own or plan to purchase an EV. Additional factors such as hearing and vision impairments, urban vs. rural living environment, and familiarity with EV technology were recorded to account for biases in auditory perception.

In the second section, participants listened to a series of EV AVAS sounds and rated them for a total set of 25 semantic scales. The semantic scales are given in Tab. 2 [1] together with the results of the principal component analysis (PCA), capturing subjective points for sound

[1] Bartlett's Test of Sphericity was significant with (x^2(25) = 1765.85, p $<$ 0.001) showing the data's suitability for PCA. KMO value p = 0.887.

attributes [2].

2.3 Categorizing Consumer Segments

Consumers in the population are divided into different subgroups, such as Early Adopters (EA) and Mainstream Consumers (MC), as stated in the work [6]. The research states that the categories are created based on the consumers' level of risk tolerance and interest in practical benefits of a product. To create the categories, the findings from the e-mobiliTI living lab experiment [7] were used.

EAs are more likely to be adopt new technologies with a lower risk perception [8]. In contrast, mainstream consumers prefer proven solutions and cost efficiency, and seek reliability before making the switch. Similarly, those who express strong concerns about the upfront cost of EVs or rely on government incentives for affordability receive higher MC points. To record these differences, the survey responses are assigned EA and MC points based on documented consumer tendencies in EV adoption [9].

EAs are also more likely to live with the challenges in EV charging and plan their trips according to this issue. Additionally, information sources and decision-making approaches further distinguish EAs from MCs. EAs tend to rely on their independent research, online sources, and social media to stay informed about new technologies. MCs are more likely to be influenced by family, friends, or dealership advertisements before making purchases [10].

Commitment to EV transition from ICE vehicles is another important aspect of adoption. EAs tend to give votes in favor of fully transitioning to EVs, replacing their conventional vehicles [11].

Brand preference is also important in EV adoption. EAs tend to select innovative, cutting-edge brands and are often willing to buy EVs from newer manufacturers. Respondents who consider the reputation of the brand highly important and follow technology innovators tends to score higher in EA points. On the other hand, for MCs, factors such as cost, reliability, and after-sales support are more important than brand innovation.

Based on the scoring method given in Tab. 3, consumer segmentation was done using k-means clustering. The process began with the standardization of the normalized EA and MC scores gathered from the consumers from the survey using z-normalization to ensure that both features contributed equally to the clustering algorithm [12, 13]. The Elbow Method was then used to determine the optimal number of clusters. This involved plotting the Within-Cluster Sum of Squares (WCSS) together with the number of clusters and identifying the "elbow point," where the rate of decrease in WCSS slows down.

[2] Component loadings with absolute values > 0.5 were highlighted to give an overview about the most significant contributors [5].

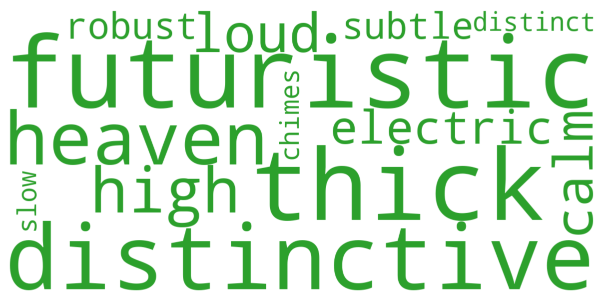

Figure 3: EV sound descriptive adjectives used by early adopters in the survey.

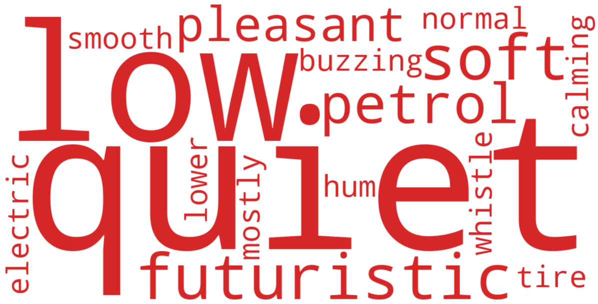

Figure 4: EV sound descriptive adjectives used by mainstream consumers in the survey.

3. RESULTS

K-means clustering algorithm was implemented following validation through the elbow method, which showed an optimal value at three clusters (WCSS reduction <5% beyond k = 3). The final clusters were analyzed through their centroid positions in the EA-MC semantic space, with additional validation from participants' open-ended responses about sound preferences. Fig. 3 and 4 visualize open-ended responses to 'How an electric car should sound?' for EAs and MCs, respectively. Results were supporting the theoretical framework of [6], which identifies

Table 3: Scoring of Survey Responses for Consumer Clustering

Survey Question	Early Adopter (EA) Points	Mainstream Consumer (MC) Points
I enjoy being among the first to try new technologies.	Score 5	Score 0
I need to see evidence that EVs work well for others before considering adoption.	Score 0	Score 5
I am concerned about the upfront cost of EVs compared to conventional cars.	Score 0	Score 5
How important are the following factors in your decision to adopt an EV?		
Range anxiety (limited driving distance per charge)	Score 0	Score 5
Lower long-term costs (e.g., fuel/maintenance)	Score 0	Score 5
Environmental impact	Score 5	Score 0
Government incentives (rebates, tax credits)	Score 0	Score 5
Access to charging stations	Score 0	Score 5
How do you typically learn about new technologies like EVs?		
Online research/articles	Score 5	Score 0
Friends/family/colleagues	Score 0	Score 5
Social media/influencers	Score 5	Score 0
Dealerships or advertisements	Score 0	Score 5
Would you replace a conventional car with an EV, or keep both?		
Replace my conventional car entirely with an EV	Score 5	Score 0
Keep both (EV + conventional vehicle)	Score 0	Score 5
Prefer a hybrid (PHEV) instead of a full EV	Score 0	Score 5
Which consumer category do you feel closest to?		
Tech-Savvy Early Adopters	Score 5	Score 0
Environmental Enthusiasts	Score 2	Score 2
Cost-Conscious Consumers	Score 0	Score 5
Affluent Luxury Vehicle Buyers	Score 2	Score 2
Urban Dwellers/Commuters	Score 2	Score 2
Consumers with Strong EV Infrastructure Access	Score 2	Score 2
How soon did you buy an EV after they became available?		
Immediately (within the first few years)	Score 5	Score 0
After seeing reviews and recommendations	Score 2	Score 2
When they became affordable & widely available	Score 0	Score 5
What was your main reason for buying an EV?		
Innovation & new technology	Score 5	Score 0
Environmental benefits	Score 5	Score 0
Cost savings & subsidies	Score 0	Score 5
Social influence or peer pressure	Score 0	Score 5
How important is brand reputation in your EV purchase?		
Very important – I follow tech innovators	Score 5	Score 0
Somewhat important – but cost/reliability matter more	Score 0	Score 5

Legend: This table shows the scoring system used to classify survey participants into two groups. Each survey response is given **points ranging from 0 to 5**.

- A **higher EA score (5 points)** indicates strong tendency to early EV adoption preferences.
- A **higher MC score (5 points)** shows a more cautious and cost-conscious standing to EV adoption.
- Some responses (e.g., Environmental Enthusiasts, Urban Dwellers) receive **equal scores (2 EA, 2 MC)** to indicate neutrality.

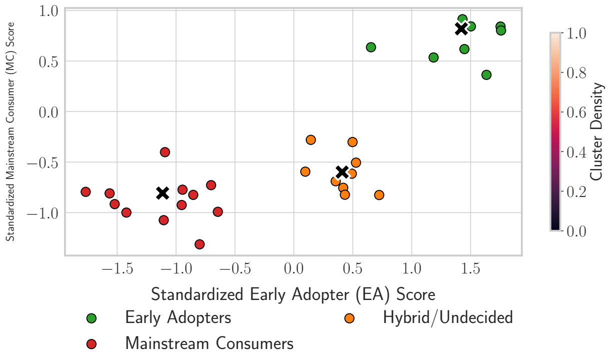

Figure 5: Participants divided into 3 different consumer clusters.

EAs, MCs, and a transitional group as adopter categories. Each respondent was assigned to the cluster with the nearest centroid, which shows the mean EA and MC scores for that cluster. The demographics of these consumer clusters are given in Fig. 6.

The analysis revealed three distinct consumer segments (Fig. 5):

- EAs (29% of sample): Characterized by high EA scores (mean (m) = 1.32, standard deviation (s.d.) = 0.28), these consumers prioritize technological novelty (ρ = 0.78, $p < 0.01$)[3] and environmental impact (ρ = 0.82, $p < 0.001$). Their sound preferences leaned toward "futuristic" (42%) and "high-tech" (38%) descriptors based on their open-ended answers.
- MCs (41% of sample): Defined by high MC scores (m =-1.05, s.d.= 0.31), this group emphasized cost sensitivity (ρ = 0.91, p<0.001) and reliability (ρ = 0.85, $p < 0.001$). Preferred sound attributes included "unobtrusive" (56%) and "familiar" (39%).
- Hybrid/Undecided (30% of sample): Showing moderate scores in both dimensions (EA: m = 0.28, MC: m =-0.41), this group showed intermediate preferences, often pointing out both to the environmental concerns (31%) and practical considerations (44%).

Significant correlations were identified between psychoacoustic parameters and subjective perceptions of

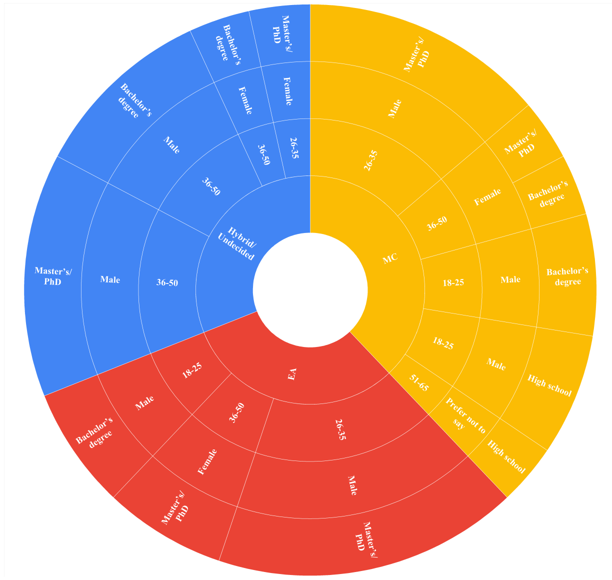

Figure 6: Demographics of the survey participants divided into consumer segments.

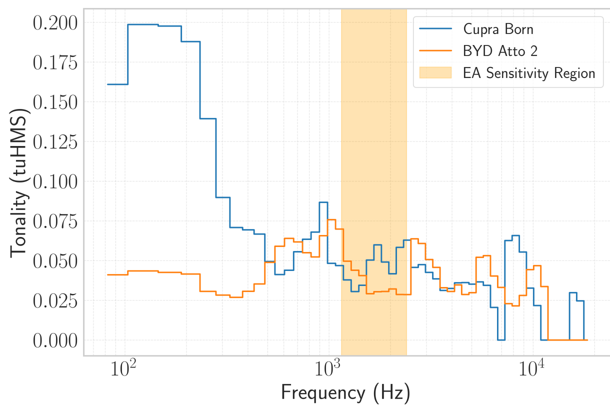

Figure 7: Tonality analysis of Sound 1 and 2.

AVAS sounds. Tonality[4] (Figure 7) exhibited a strong positive relationship with ratings of "futuristic" (r = 0.89, p = 0.043), with high-tonality sounds in mid-high Bark bands (8.5 – 12.5, $p < 0.01$) such as Sound 2 and Sound 1 consistently described as innovative and technologically advanced. These two sounds were also strongly favored by EAs with their high-tonality and futuristic profiles (m = 4.5) compared to MCs based on a one-way ANOVA anal-

[3] The bootstrapped (1000 resamples) pearson correlation for all ρ.

[4] Hearing model.

ysis (m = 2.3, F(2,26) = 12.7, $p < 0.001$.)[5] EAs also rated "annoying" lower for these sounds (p = 0.002), indicating a tolerance for artificiality when aligned with innovation. These results contradict with answers given by MCs, who rated them as more annoying ($p < 0.01$)[6]. MCs prioritized unobtrusive sounds, favoring Sound 4 for its quietness (m = 6.5 for "quiet," p = 0.002)[7] and reduced fluctuation strength (Figure 8) in mid-low Bark bands (2.5 – 6.5 , p = 0.03).

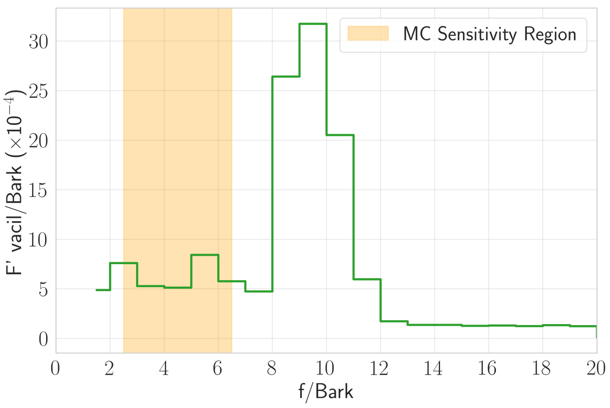

Figure 8: Fluctuation strength analysis of Sound 4.

4. DISCUSSION

The results of the study built on the current status quo which has showed the significance of combining consumer perception with sound engineering, as technical acoustic parameters often fail to capture the full user experience [1]. The present study improves this idea by applying psychoacoustic modeling to AVAS sounds in EVs, revealing that different consumer segments show distinct preferences for tonal attributes of these sounds.

One of the important findings of this research is the difference in perception between EAs and MCs. EAs tend to associate high-tonality sounds with futuristic and technologically advanced vehicles, which is consistent with the findings in [14],which showed the role of psychoacoustic factors in the perceived modernity of vehicle sounds. MCs prefer quieter and unobtrusive sounds, supporting the work in [15], showing that consumer satisfaction is influenced by the perceived naturalness of synthetic sound elements.

Previous studies have shown that different cultural backgrounds and exposure to varying noise environments build individual preferences for vehicle sounds [16]. This research improves this knowledge by demonstrating that personal driving habits and familiarity with EVs further modulate AVAS sound acceptability. This is important in the context of designing globally acceptable AVAS solutions, as advocated by [17], which proposed an approach, including soundscape and psychoacoustic modeling to optimize auditory comfort.

Furthermore, the findings show that sound preference is not only explained by technical performance but also by emotional and cognitive associations. A literature review in [18] emphasized that psychoacoustic models must include subjective perception criteria, as users interpret sounds based on prior experiences and expectations. The correlation between psychoacoustic parameters and descriptors such as "futuristic" and "annoying" in this study supports the previous research suggesting that emotional connections influence the acceptability of artificial vehicle sounds [19].

5. CONCLUSION

The integration of psychoacoustic modeling with consumer-driven semantic attribute development presents a novel and effective method for optimizing AVAS sounds. The study shows the importance of applying user categorization, and emotional attributes in sound perception. Consumer groups exhibited statistically distinct preferences ($p < 0.05$ for 7/10 attributes), with psychoacoustic differences localized to specific Bark bands. According to the results reported in Chapter 3, designers may optimize tonality above 8.5 Bark to enhance "Futuristic" perceptions to capture the interest of the EA population. For MCs, fluctuation strength below 6.5 Bark should be minimized which contributes to quiteness and calmness semantics for this user group. These designs changes can be validated for a future step to this study.

6. ACKNOWLEDGMENTS

This work was supported by the Joint project 6G-life, under Grant 16KISK001K and as a part of Germany's Ex-

[5] Post-hoc: EA > MC ($p < 0.001$), EA > Hybrid (p = 0.003).

[6] ANOVA: F(2, 26) = 9.4, p = 0.001. Post-hoc: MC > EA (p = 0.002), Hybrid > EA (p = 0.012).

[7] Kruskal-Wallis: H = 9.4, p = 0.002. Post-hoc: MC > EA (p = 0.001), MC > Hybrid (p = 0.015).

cellence Strategy – EXC 2050/1 – Project ID 390696704 – Cluster of Excellence "Centre for Tactile Internet with Human-in-the-Loop" (CeTI) of TU Dresden.

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